

Noise Removal in Magnetic Resonance Images using Hybrid KSL Filtering Technique

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ABSTRACT

In Medical Diagnostic, Magnetic Resonance Images play a major role. Magnetic Resonance images are normally corrupted by random noise from the measurement process complicating the automatic feature extraction and analysis of clinical data. Because of this reason noise removal methods have been customarily applied to improve MR image quality. This work proposed a new scheme based on applying a series of filters, each used to modify the estimate into greater agreement, so that the output converges to a stable estimate providing noise free image. In this work, we have introduced a novel hybrid filter to reduce random noise in MR images by the combination of Kernel, Sobel and Low-pass (KSL) filtering techniques. The proposed method has been implemented using Matlab and compared with related state of art methods over synthetic and real clinical MR images showing a superior performance in all cases analyzed.

General Terms: Noise Removal – Magnetic Resonance Images.

Keywords: Kernel Operator, Low-pass Filter, Noise Removal, Sobel Operator.

1. INTRODUCTION

Noise removal is the process of removing noise from a signal. Noise reduction techniques are theoretically comparable regardless of the signal being processed. Image denoising is often used in the field of publishing or photography where an image was degraded somehow but needs to be enhanced before it can be printed. Denoising is playing an important role in Medical image enhancement also.

Retrieving a high quality MR Image for a medical diagnostic is critical, because it injures human more if we pass high level Magnetic resonance sound to take the image. So denoising of magnetic resonance (MR) images is a challenging issue. MR images are normally corrupted by thermal noise, sample resolution, etc. Understanding the spatial distribution of noise in an MR image is very difficult to any attempt to calculate approximately the true signal. The investigation of how noise is distributed in MR images is chronological.

2. RELATED WORKS

Various algorithms used for image denoising are discussed in [1]. The de-noising of Magnetic Resonance Images using wave atom shrinkage is proposed in [2] and also proved that this approach achieves a better SNR compared to wavelet and curvelet shrinkages. A NL-Denoising method for Rician noise reduction is proposed in [3 & 4]. In [5], a test bed for baseline

correction and noise filtering methods is implemented and compared. In [6] a nonparametric Neighborhood Statistics method is proposed for MRI Denoising. An adaptive wavelet-based Magnetic Resonance images denoising algorithm using wavelet shrinkage and mixture model concept is introduced in [7]. The method to improve image quality based on determining the critical pulse sequence parameters by timing constraints from all gradients, rather than a single gradient of the image has been given in [8]. A new filter to reduce random noise in multicomponent MR images by spatially averaging similar pixels and a local principal component analysis decomposition using information from all available image components to perform the denoising process is proposed in [9]. A new signal estimator based upon the technique of "noise cancellation", which is commonly used in signal processing is used to recover signals corrupted by additive noise in MRI is proposed in [10]. An estimator using a priori information for devising a single dimensional noise cancellation for the variance of the thermal noise in magnetic resonance imaging (MRI) systems called ML estimator has been proposed in [11]. Non-Local Means (NLM) filtering method for reducing artifacts caused in MRI due to under sampling of k-space (to reduce scan time) is proposed in [12]. A maximum a posteriori estimation technique that operates directly on the diffusion weighted images and accounts for the biases introduced by Rician noise is introduced in [13] for filtering diffusion tensor magnetic resonance images. A novel approach to evaluating reconstructions for low-SNR magnetic resonance (MR) images is given in [14]. A filtering process based on anisotropic diffusion is presented in [15]. A spatially adaptive TV model has been applied to partially parallel MRI (PP-MRI) image reconstructed using GRAPPA (generalized approach to parallel magnetic resonance imaging) and SENSE (Sensitivity encoding MRI Imaging) is proposed in [16]. The novel filtering method known as trilateral filtering (TF) is proposed in [17 and 18] works similar as Bilateral Filtering and takes the geometric, photometric and local structural similarities to smooth the MR images. A noise removal technique using 4th order PDE is introduced in [19] to reduce noise in MRI images. A phase error estimation scheme based on iteratively applying a series of non-linear filters each used to modify the estimate into greater agreement with one piece of knowledge, until the output converges to a stable estimate is introduced in [20]. A wavelet-based multiscale products thresholding scheme using Dyadic Wavelet Transform for detecting Multiscale Edge is introduced in [21] for noise suppression of magnetic resonance images. Our proposed work introduces a hybrid filtering technique combining sobel, kernel and low-pass filters to produce a noise-reduced MRI image.

3. METHODOLOGY AND DESIGN

There is lots of image processing and statistical and machine learning techniques involved in the design of the proposed system.

3.1 Proposed Model of the Noise Reduction System

Fig 1 shows the proposed model of the Noise Reduction System.

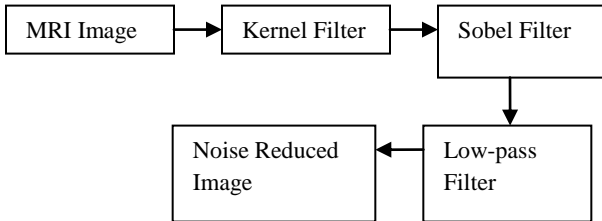


Fig 1: Model of the Noise Removal system

3.2 Techniques used in Proposed Model

3.2.1 Sobel Filter

The Sobel operator performs a 2-D spatial gradient measurement on an image. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). A convolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time. The actual Sobel masks are shown below:

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$$

and

$$G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The magnitude of the gradient is then calculated using the formula,

$$|G| = \sqrt{G_x^2 + G_y^2}$$

An approximate magnitude can be calculated using:

$$|G| = |G_x| + |G_y|$$

3.2.2 Kernel Filter

A kernel filter works by applying a kernel matrix to every pixel in the image. The kernel has multiplication factors to be used to the pixel and its neighbors. Once all the values have been multiplied, the pixel is changed with the sum of the products. By choosing different kernels, different types of filtering can be

applied. Kernel filters provide low and high-pass filtering using a kernel.

Fig 1 : Sample Image and its Corresponding Histogram

3.2.3 The Low-pass Filter

3.2.4 A low pass filter is the basis for most smoothing methods. An image is smoothed by decreasing the disparity between pixel values by averaging nearby pixels. Using a low pass filter tends to retain the low frequency information within an image while reducing the high frequency information. An example is an array of ones divided by the number of elements within the kernel, such as the following 3 by 3 kernel:

$$\begin{bmatrix} -1/16 & -1/8 & -1/16 \\ -1/8 & 3/4 & -1/8 \\ -1/16 & -1/8 & -1/16 \end{bmatrix}$$

Proposed Hybrid KSL Filtering for MRI Noise removal method:

Input: Input Image

Output: Noise Reduced Image

Algorithm :

- Step 1: Accept the input image
- Step 2: Apply mask G_x,G_y to the input image
- Step 3: Apply Kernel edge detection algorithm
- Step 4: Masks manipulation of G_x,G_y separately on the input image
- Step 5: Apply Sobel edge detection algorithm and the gradient
- Step 6: Masks manipulation of G_x,G_y separately on the input image
- Step 7: Apply Low-pass filter
- Step 8: Masks manipulation of G_x,G_y separately on the input image
- Step 9: Combine the filter Results to get a noise free output image.

4. RESULTS & DISCUSSION

The proposed hybrid filtering KSL filtering algorithm is implemented in Matlab and tested with sample MRI clinical images and producing noteworthy results. Experimental results of this work can be discussed by seeing an example.

Step 1: Read the MRI image to reduce the noise (Fig 2).

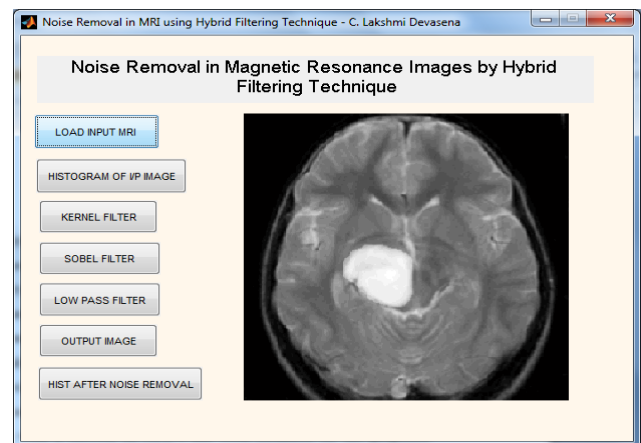


Fig 2: Load Input MRI Image

Step 2: After reading the image, the existence of noise can be verified by seeing its histogram as shown in Fig 3.

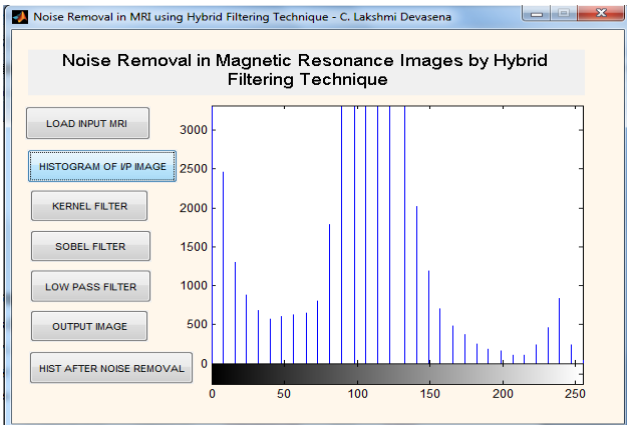


Fig 3: Histogram of the Input MR Image.

Step 3: Apply the kernel filter to the input image. The result of Kernel Filter is shown in Fig 4.

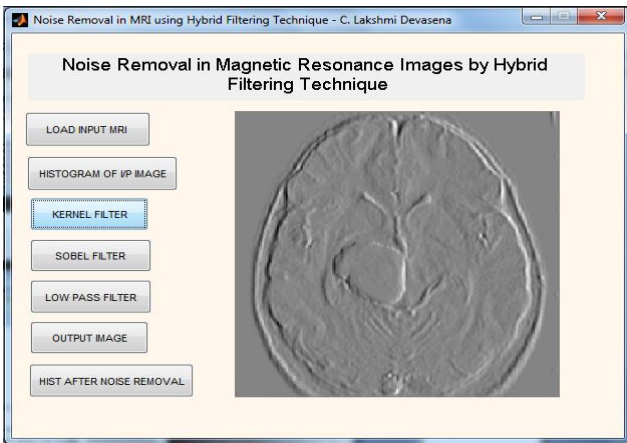


Fig 4: Result of Kernel Filter

Step 4: Apply the Sobel filter to the input image. The result of Sobel Filter is shown in Fig 5.

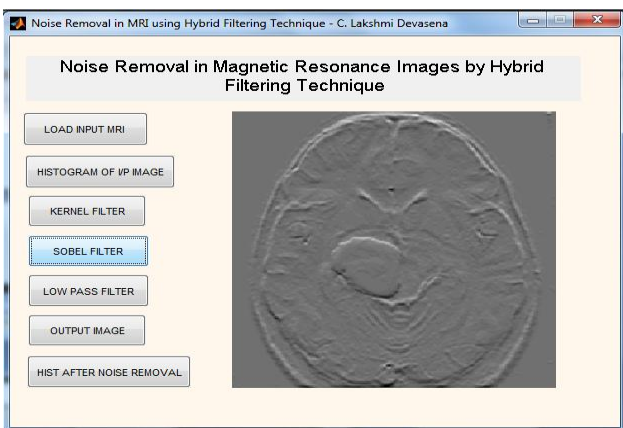


Fig 5: Result of Sobel Filter

Step 5: Apply the Low-pass filter to the input image. The result of Low-pass Filter is shown in Fig 6.

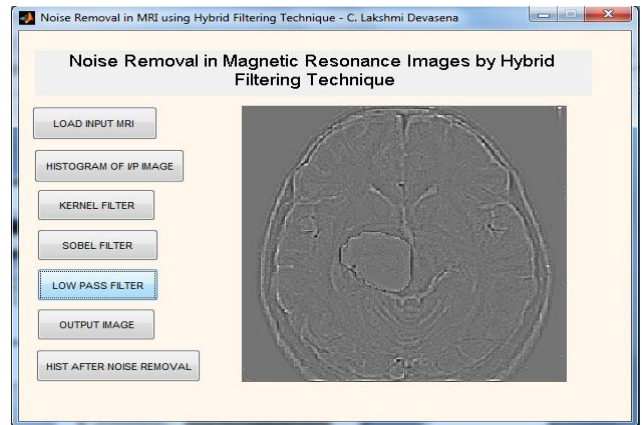


Fig 6: Result of Low-pass Filter

Step 6: Combine the filter results to get the noise free MR output image as shown in Fig 7.

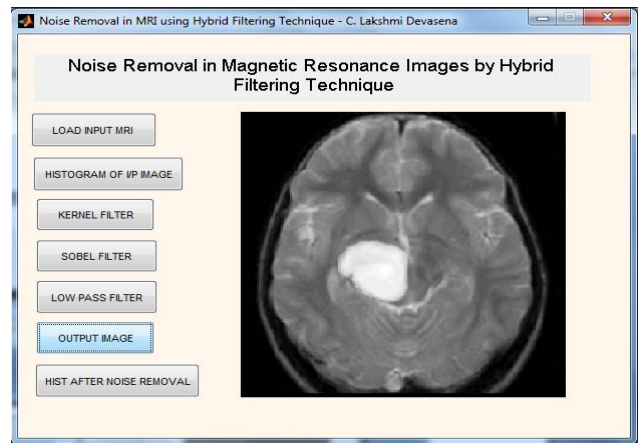


Fig 7: Noise Free output of the proposed method.

Step 7: Now we can verify the existence of noise in the produced output image by comparing its histogram. The histogram of the output image is shown in Fig 8. Now we can notify the difference between two histograms and ensure the removal of noise.

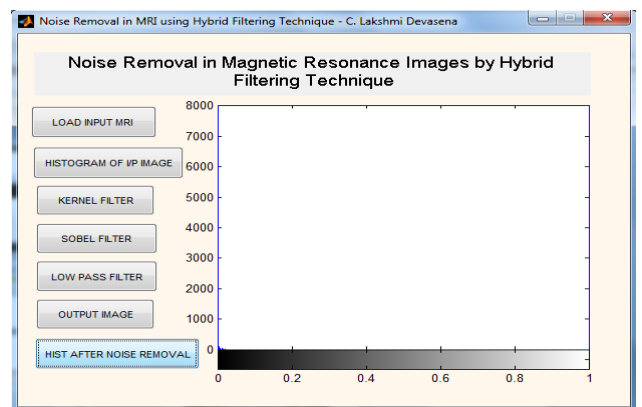


Fig 8: Histogram of the resulting image.

5. CONCLUSIONS

The proposed hybrid KSL filtering technique for noise removal in Magnetic Resonance images is implemented in Matlab and tested with different synthetic and real clinical MRI images and producing promising results. This method could be used to reduce the noise in different type of MRI images like low-SNR MR images, partially parallel MRI images and so on. The output of this method has been compared with other filtering methods and shows superior performance.

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